Reinforcement Learning for Building Control: Direct Actuator or PI-Mediated Control?

A Systematic Comparison Using BOPTEST Framework

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Why This Matters

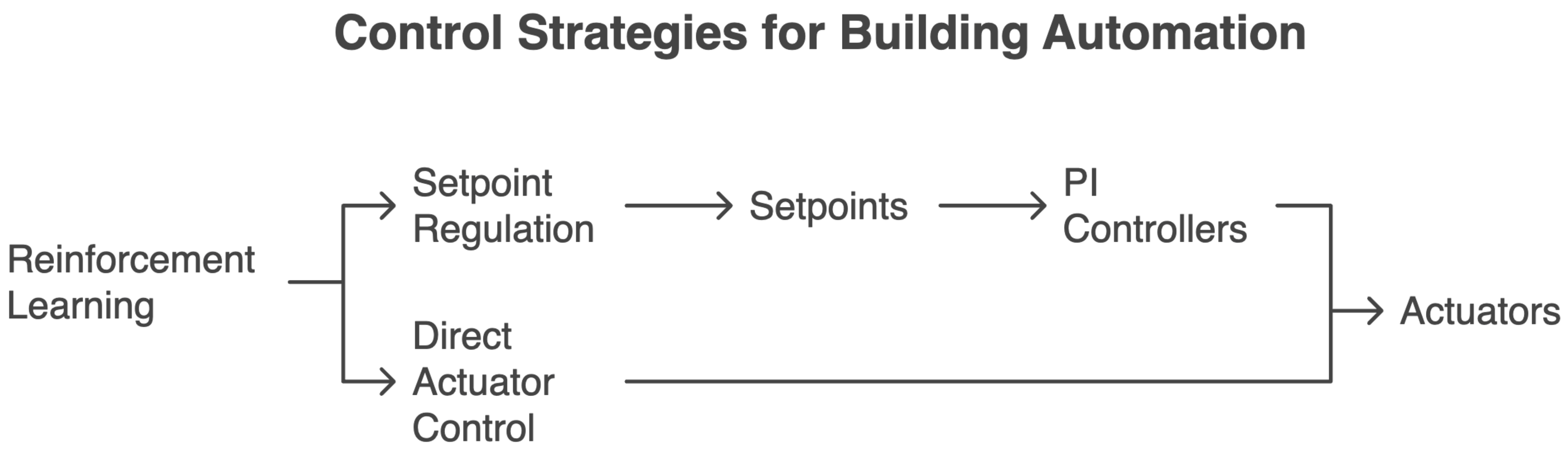
- **40% of global energy consumption** comes from buildings
- Traditional PI controllers **lack predictive capabilities** for optimal energy-comfort trade-offs
- Reinforcement Learning shows promise but lacks systematic evaluation

Current Research Gap

- Most studies focus on **single control paradigm**
- Limited **empirical comparisons** between approaches
- Lack of **standardized evaluation** across building types

Fundamental Question: Should RL agents control setpoints or directly command actuators?

Two Control Paradigms



Setpoint Regulation (SR) vs Direct Actuator Control (DAC) architecture

Setpoint Regulation (SR)

- Stable, proven architecture
- Leverages existing building automation
- Preserves low-level control expertise
- Built-in safety mechanisms
- Easier integration

Direct Actuator Control (DAC)

- Larger solution space
- No cascading errors
- Full control authority
- Potentially optimal strategies
- Direct optimization

Research Challenge: Which approach offers better training efficiency, control stability, and energy performance in realistic building scenarios?

Research Questions

- **Energy Efficiency**: How do trade-offs differ between approaches across building types?
- **Thermal Comfort**: What are the comfort achievement and violation patterns?
- **Training Efficiency**: Which approach converges faster and requires fewer samples?
- **Control Stability**: How does operational robustness compare between paradigms?

Goal: Provide quantitative evidence to guide practical RL deployment in real-world building control systems

Methodology

Experimental Framework

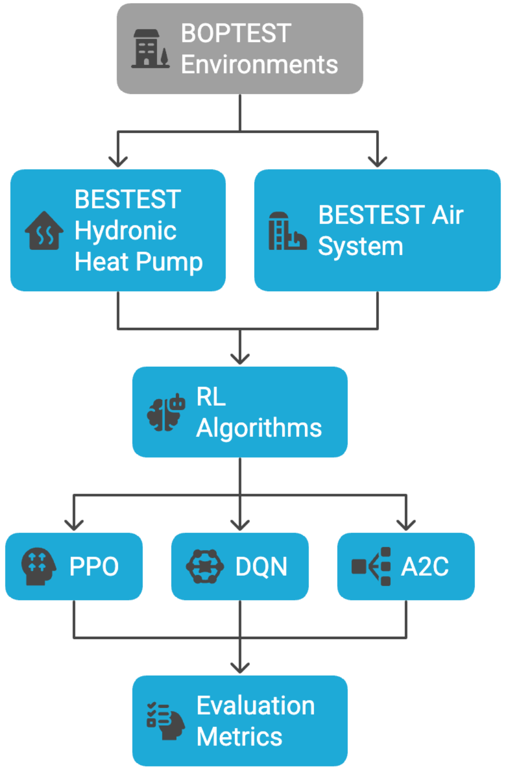
BESTEST Hydronic Heat Pump

- Single-zone residential building
- Heat pump + radiant floor heating
- Complex thermal dynamics

BESTEST Air System

- Variable air volume HVAC
- Heating and cooling coils
- Fast-response system

BOPTEST Experimental Framework



Reinforcement Learning Formulation

State Space: Zone temperature, weather conditions, time features, electricity pricing

Action Space: 30-bin discretization for fair comparison

Reward Function:

$$R_t = -(O_t - O_{t-1})$$

$$\text{where } O_t = \text{cost\_tot} + \text{tdis\_tot}$$

Control Paradigm Implementation

Both paradigms use identical:

- **State spaces**: Zone temperature, weather, time features
- **Training protocols**: 10M steps, 1-hour control periods
- **Evaluation metrics**: Energy cost, thermal comfort, training efficiency

Key Differences

- SR: Temperature setpoints (5-35°C)
- DAC: Direct actuator commands (0-1 range)

Control Paradigm Comparison

Characteristic	Setpoint Regulation	Direct Actuator Control
Action Mapping - Hydronic Heat Pump	Temperature setpoint (oveTSet_u)	Heat pump control signal (oveHeaPumY_u)
Action Mapping - BESTEST Air	Cooling + heating setpoints (con_oveTSetCoo_u, con_oveTSetHea_u)	Fan speed + supply temperature (fcu_oveFan_u, fcu_oveTSup_u)
Range	5-35°C discretized into 30 bins	0-1 discretized into 30 bins
Control	PI controllers translate setpoints → actuator commands	Direct actuator command without intermediate control layer

Results

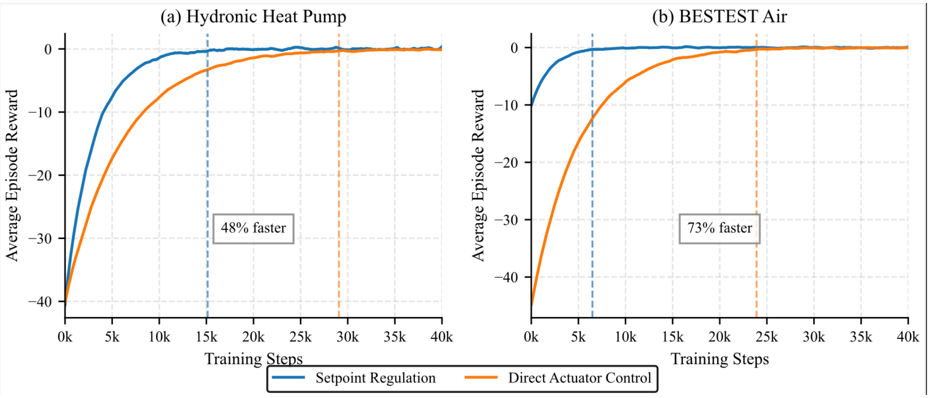
Energy vs. Comfort Trade-offs

ENVIRONMENT	METHOD	ENERGY COST	THERMAL DISCOMFORT	IMPROVEMENT
Hydronic Heat Pump	SR	0.924 (+4.8%)	0.00 (-100%)	Perfect comfort
	DAC	0.898 (+1.8%)	1.63 (-80.6%)	Balanced
	Baseline	0.882	8.38 Kh	Poor comfort
BESTEST Air	SR	0.210 (+5.0%)	(0.04) -99.3%	Near-perfect
	DAC	0.206 (+3.2%)	1.09 (-80.8%)	Efficient
	Baseline	0.200	5.69 Kh	Poor comfort

Key Finding: Consistent pattern across building types - SR prioritizes comfort, DAC balances energy-comfort trade-offs

Training Efficiency Comparison

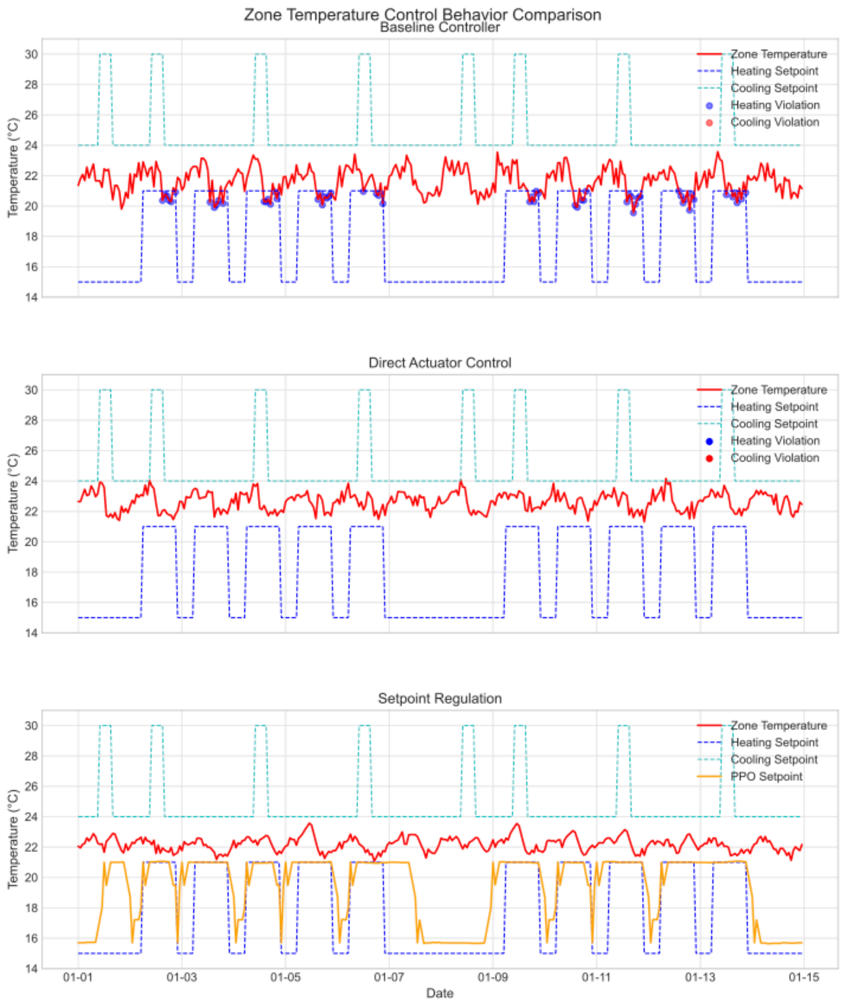
METHOD	SR STEPS	DAC STEPS	IMPROVEMENT
PPO (Hydronic)	8,200	15,800	**48% faster**
PPO (Air)	6,800	25,200	**73% faster**
DQN (Hydronic)	7,500	18,700	**60% faster**
DQN (Air)	7,200	24,500	**66% faster**
A2C (Hydronic)	**6,900**	16,200	**61% faster**
A2C (Air)	**5,900**	28,100	**79% faster**



Control Paradigm Implementation

Control Stability Analysis

METRIC	SR	DAC	BASELINE
Control Variance	-38%	+34%	0%
Cycles/Day	3.9	6.3	4.7
Stability	Best	worst	Frequent



Key Findings

- **Superior stability:** 38% lower control variance
- **Reduced cycling**: Extends equipment life
- **Perfect comfort**: Maintains temperature band
- **Operational efficiency**: More stable behavior

Why Setpoint Regulation Excels

1. Incorporates System Knowledge

Pre-existing PI controllers encode thermal response characteristics through tuned parameters (Kp, Ki), providing useful inductive biases for learning

2. Structured Optimization Problem

Clearer action-response relationships with constrained, reasonable setpoint ranges create smoother reward landscapes

Result: 48-79% reduction in training steps across algorithms and environments, with 38% lower control signal variance

Discussion & Impact

Technical Innovations

- **First systematic comparison** of SR vs DAC in building control
- **Standardized evaluation** using BOPTEST framework across building types
- **Quantitative training efficiency analysis** with consistent methodology

Practical Insights

When to Choose SR

- Comfort-critical applications
- Limited training data/time
- Existing building automation
- Risk-averse deployments

When to Consider DAC

- Energy-focused objectives
- New system installations
- Research/experimental settings
- Specialized control requirements

Limitations & Future Work

Current Study Limitations

- **Simulation-based evaluation** may not capture all real-world complexities
- **Constant electricity pricing** - dynamic pricing effects unexplored
- **Fixed comfort-energy weighting** in reward function
- **Single-zone buildings** - multi-zone coordination unexplored

Future Research Directions

- **Hybrid approaches**: Dynamic switching between SR and DAC based on conditions
- **Multi-zone systems**: Coordination challenges in larger buildings
- **Real-world validation**: Pilot deployments in actual buildings
- **Transfer learning**: Cross-building knowledge transfer

Conclusion

Training Efficiency Champion: Setpoint Regulation

48-79% fewer training steps across all algorithms and environments, with superior control stability (38% lower variance)

Control Stability and Performance Pattern

SR: Superior stability with 38% lower control variance and 3.9 cycles/day vs 6.3 for DAC
DAC: Higher control variance but direct optimization capability with 1.8-3.2% energy increases

Algorithm Winner: A2C

Consistently fastest convergence and best performance across both control paradigms

Thank You

Questions & Discussion

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