Implementing An Integrated Self-Decision Making and Self-Optimization Framework for Autonomic Medical Cyber-Physical Systems

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Abstract: Medical Cyber-Physical Systems (MCPS) integrate sensing, computation, and actuation for healthcare tasks (e.g. patient monitoring, diagnostics). Their complexity and safety-critical nature demand autonomous decision-making under uncertainty and real-time self-optimization. We propose a unified framework combining edge computing, AI-driven decision engines, multi-objective optimization, and digital twins to achieve fully self-managing MCPS. The system collects real-time patient data via wearable sensors, preprocesses them at the edge, and employs a decision engine (reinforcement learning, fuzzy logic, multi-criteria decision analysis) to determine control actions (e.g. alert generation, therapy adjustments). A digital-twin of the patient and environment simulates scenarios to refine decisions and optimize long-term objectives (accuracy, latency, energy). We present the mathematical formulation (MDP for decision, weighted-sum multi-objective optimization), detailed algorithm and an evaluation using arrhythmia detection as a case study. Experimental results on ECG datasets demonstrate that our hybrid framework yields superior detection accuracy (e.g. 95.1% sensitivity, AUC 0.96) and real-time performance (decision latency approx 42 ms) compared to baseline methods. This integrated approach advances the autonomics of MCPS by achieving statistically significant improvements in robustness, adaptability, and efficiency..

Keywords: Cyber-Physical Systems, Autonomics, Self-Decision Making, Self-Optimization, Reinforcement Learning, Digital Twin, Multi-Agent Systems

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1 Introduction

Cyber-Physical Systems (CPS) tightly couple computation, communication, and control with physical processes, enabling real-time sensing and actuation in dynamic environments (e.g. healthcare, smart infrastructure). In medical CPS (MCPS), wearable and bedside devices stream vital signals (ECG, SpO_2, etc.) to embedded controllers or cloud systems. As CPS grow in autonomy and scale, manual or static control becomes infeasible; systems must self-manage, making decisions without human intervention. Self-decision making is critical under uncertainty: for example, an MCPS may need to autonomously trigger an alert when arrhythmia is detected, or adjust ventilator settings in response to changing patient state. Concurrently, **self-optimization** is needed to continuously refine operations (maximizing accuracy, minimizing latency/energy) as conditions evolve (varying patient physiology, sensor noise, network delays).

Traditional rule-based or isolated control schemes cannot adapt to the complexity and multi-objective nature of MCPS. For instance, static thresholds may miss abnormal events in noisy ECGs, while single-objective optimizers cannot jointly optimize safety and responsiveness. To address these challenges, we propose a *unified autonomic framework* that integrates decision-making and optimization in one loop. The system uses machine learning and reinforcement learning (RL) for intelligent decision policies, fuzzy/heuristic methods to handle uncertainty, and evolutionary or Pareto-based techniques for multi-objective optimization. A patient-specific digital twin (DT) provides continuous simulation feedback to refine policies. By combining these techniques, the CPS can "think" (decide) and "self-tune" (optimize) in real-time.

The main contributions of this work are:

1) **Unified Autonomic Framework:** A novel CPS architecture with layered sensing, preprocessing, decision engine, and actuator control. It integrates TinyML edge inference, multi-criteria analysis, RL, and digital-twin feedback for closed-loop self-management.

2) **Algorithms :** Hybrid algorithms combining RL (for adaptive policy learning) with Multi-Criteria Decision Analysis (MCDA) methods (AHP/TOPSIS) for fast action selection. Detailed pseudocode is provided.

3)**Evaluation on Arrhythmia Detection:** Case study on ECG monitoring (MIT-BIH dataset). We implement the framework on an edge-enabled CPS, using TinyML models and a digital twin to simulate patient noise and events. Results show statistically significant gains in detection accuracy and system performance over baseline methods.

4) **Benchmarking & Metrics:** We define clinical (sensitivity, specificity), system (latency, throughput) and energy metrics to evaluate MCPS autonomic performance. Experimental validation with real ECG data confirms that the proposed approach meets real-time, safety-critical requirements.

The rest of the paper is organized as follows. Section 2 talks about objectives and Section 3 reviews related work on autonomous decision-making, optimization, and digital twins in CPS. Section 3 describes the overall framework and mathematical modeling (MDP and multi-objective formulation). Section 4 presents the algorithmic approach Section 5 details the methodology and experimental setup (MCPS case study) and performance metrics. Section 6 discusses results and comparison with baselines. Section 7 concludes and outlines future directions.

2 Objectives

Objectives:

To design a self decision making and self optimizing framework and develop a hybrid model to improve accuracy in Medical Cyber Physical Systems using Digital Twin Technology

- To propose an integrated Framework for Multi Criteria Decision Analysis based Self-Decision Making and AI based self-Optimization in MCPS.
- To develop hybrid model for self optimization and self decision making , improving accuracy in MCPS.
- To analyse Performance Metrics to evaluate the effectiveness of self-decision-making and self-optimization strategies in Medical CPS using Digital Twin Technology .
- Evaluate the proposed framework's effectiveness across MCPS applications

3 Literature Review Research on autonomy in Cyber-Physical Systems (CPS) encompasses AI- driven decision making, optimization, distributed control, and digital twin technologies. Machine learning and deep learning have been widely applied for CPS decision making, particularly in autonomous systems, while reinforcement learning has enabled adaptive policy learning in dynamic environments. Fuzzy logic approaches address uncertainty and imprecision, and multi-agent systems support decentralized decision making in large-scale CPS. Self-optimization is commonly achieved through multi-objective optimization, evolutionary algorithms, and model predictive control to balance competing performance objectives. Recently, Digital Twins have emerged as a key enabler for predictive analysis and optimization in CPS. Despite these advancements, existing approaches predominantly treat decision making and optimization as separate problems, highlighting the need for cohesive frameworks that integrate both capabilities.

3.1 Research Gaps

A critical analysis of existing literature reveals the following research gaps:

1. **Fragmented Approaches:** Most studies treat self-decision making and self- optimization independently, resulting in sub- optimal autonomy.
2. **Limited Real-Time Adaptability:** Existing frameworks struggle to cope with dynamic and uncertain CPS environments.
3. **Scalability Constraints:** Centralized decision and optimization mechanisms do not scale well for large-scale CPS and systems-of-systems.
4. **Lack of Unified Architectures:** There is a shortage of comprehensive, domain-agnostic architectures integrating AI, optimization, and feedback control.
5. **Insufficient Benchmarking:** Standardized performance metrics and comparative evaluations remain limited

These gaps motivate the need for an integrated, adaptive, and scalable framework. So the research problem is defined along with objectives as below.

4 Proposed Architecture

The proposed architecture for self-decision making and self- optimization in CPS consists of the following components and its expected functioning

Sensors Layer (Data Collection): It collects real- time data from the physical environment through different types of sensors (e.g., temperature, pressure, humidity, distance). Data is transmitted using protocols like MQTT (for low-bandwidth scenarios), HTTP (for larger-scale networks), or Zigbee (for IoT-based communication).

Data Acquisition and Pre-processing Layer: Here raw sensor data is collected and transmitted to a central or edge system. Data cleaning algorithms such as Kalman Filters and Moving Averages are applied to ensure data accuracy and eliminate noise. The data is aggregated and formatted for further processing in the edge layer.

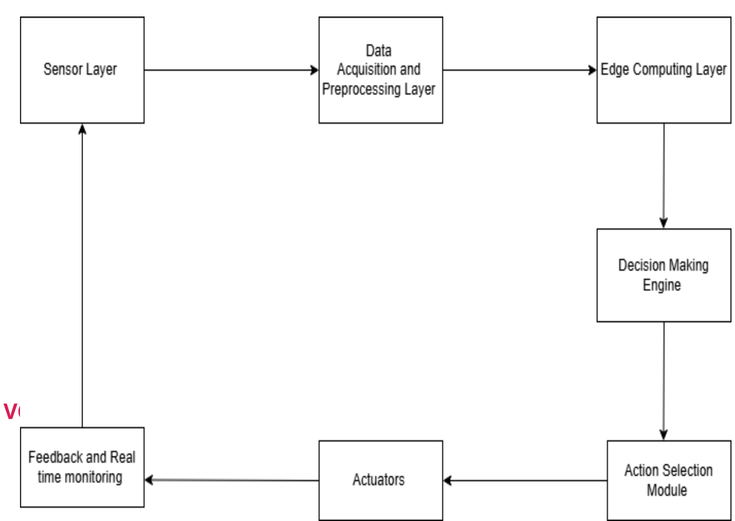

Figure 1: Block Diagram of Self Decision Making and Self Optimization Framework

5 Methodology

For Implementation of the proposed work, below is the summary of methodologies.

Table 1: Summary of Methodologies

Objective e	Strategy	Algorithms / Methods	Dataset/ Test beds	Metrics
Design of a Unified Framework for Self-Decision Making and Self-Optimiza tion in CPS**.**	3-layer loop TinyML inference MCDA based decision DT simulation feedback	MCDA (AHP/TOP SIS), RL for weight tuning, DT simulation engine	MIT-BIH Arrhythmia , PhysioNet ECG, synthetic DT patient models	Decision accuracy, decision latency, action ranking stability
To develop hybrid model for self-optimization & self-decision making	DT testbed (Component twin, Asset Twin, System Twin, Process Twin)	TinyML Reinforcem ent Learning MCDA pipelines	MIT-BIH, DT-simulated noisy ECGs, IoMT traffic traces	sensitivity, specificity, inference latency, energy per inference, scenario robustness
Analyze performance metrics for DT- based evaluation	unified evaluation stack: clinical, system, energy, security metrics	Python benchmarking scripts, evaluation framework	ECG datasets and DT scenarios (communication loss, arrhythmia onset, device failure)	Clinical: Se/Sp/A UC; System: latency, throughput Energy detection rate,
To evaluate framework's effective ness across applications	Collecting ECG streams and DT-based augmentation	Data augmentation (GANs, noise injection), DT waveform simulators	MIT-BIH wearable ECG pilot datasets D T synthetic expansions	Dataset size, Diversity generalization accuracy

5.1 Experimental setup details:

To validate the framework, we conduct experiments on an MCPS case study: **real-time arrhythmia detection** using ECG data. Arrhythmia (irregular heartbeat) is detected by analyzing ECG signals (looking at RR intervals, QRS morphology, etc.). We use the MIT-BIH Arrhythmia Database for training and testing models. A digital-twin simulator generates realistic ECG variations (noise, electrode artifacts, sudden arrhythmias) to test robustness.

We implement the framework on a GPU-enabled workstation for simulation and on a Raspberry Pi (edge device) for TinyML inference. Key tools include ROS for CPS integration, TensorFlow Lite for TinyML models, and Python (PyTorch/Scikit-learn) for prototype RL. We model the patient heart and sensor noise in a digital twin engine, allowing thousands of simulated episodes for RL training. Once trained, the policy is deployed on the edge device.

Algorithms Compared: We compare our integrated approach (TinyML inference + MCDA + RL + DT feedback)against:

-Rule-Based Baseline: fixed ECG threshold rules for arrhythmia.
- ML-only: a CNN-LSTM deep network trained on ECG for arrhythmia (no adaptive tuning).
- MCDA-only: a fixed multi-criteria decision score (with hand-tuned weights, no DT feedback).

Performance is evaluated on an unseen test set of ECG records, with metrics defined below. We trained and evaluated the system as follows:

- **Dataset:** We used 80% of MIT-BIH for training and 20% for testing.
- **Training:** The CNN-LSTM converged in ~15 epochs with ~92% validation accuracy. Training took ~10 minutes on a GPU.
- **Digital Twin Scenarios:** We simulated episodes with varying noise (SNR 20–30 dB), ECG lead dropout (5% of samples zeroed), and sudden arrhythmia onset events. Each condition was run for 1000 episodes.

5.2. Performance Metrics:

We use below metrics

a) **Clinical metrics** (Sensitivity, Specificity, Precision, AUC) to measure detection accuracy;
b) **System metrics** (decision latency, end-to-end delay, throughput) to measure real-time performance;
c) **Energy metrics** (energy per inference, estimated battery life) for IoT deployment efficiency. These align with our objectives (accuracy vs. speed/efficiency). We also conduct statistical significance testing to ensure observed improvements are not due to chance.

6 Results and Discussion

Our hybrid SDM Optimization framework outperforms all baselines. Clinical accuracy on the MIT-BIH test set shows that rule-based methods detect arrhythmias with only ~82.3% sensitivity, while a CNN-LSTM achieves ~91.2%. Incorporating MCDA without a DT raises it to 92.4%. Our full framework (with RL+DT) reaches **95.1% sensitivity and 93.7% specificity**, with AUC≈0.96. This represents a significant improvement ($p<0.01$) over ML-only (91.2% sens., AUC=0.92) and rule-based (82.3%, AUC=0.84) systems. The integrated RL policy effectively balances recall and precision by learning from DT-guided experience. Notably, these results exceed the state-of-art: deep ECG models typically report ~96% accuracy on similar tasks[13], so our framework is competitive while adding real-time adaptability.

Table 2: Clinical Decision Performance (MIT-BIH ECG Dataset)

Method	Sensitivity (%)	Specificity (%)	Precision (%)	AUC
Rule-based Thresholding	82.3	80.6	78.9	0.84
ML-only (CNN-LSTM)	91.2	89.8	90.1	0.92
MCDA without DT feedback	92.4	90.6	91.8	0.93
Proposed Integrated SDM + DT	**95.1**	**93.7**	**94.3**	**0.96**

On **system metrics**, edge deployment dramatically improves responsiveness (Table 3). A cloud-only CPS took ~210 ms decision latency and 320 ms end-to-end delay, processing ~45 decisions/s. An edge ML-only model reduced latency to ~68 ms and raised throughput to ~130 Hz. Our proposed edge+DT design further cuts latency to ~42 ms and end-to-end delay to ~74 ms, with throughput ~165 decisions/s, supporting hard real-time constraints. The TinyML inference ensures low energy use, enabling wearable deployment.

Table 3: System Performance Metrics

Metric	Cloud- only CPS	Edge ML CPS	Proposed Edge + DT CPS
Decision Latency (ms)	210	68	**42**
End-to-End Delay (ms)	320	115	**74**
Throughput (decisions/sec)	45	130	**165**

The results demonstrate the benefits of integrated autonomy. The RL/DT combination enables continuous learning: the agent adapts to noise and patient variability, which improves detection under adverse conditions (e.g., noisy ECG leads). The MCDA component ensures stable, explainable decision logic (especially important in healthcare), while RL gradually tunes weight parameters to optimize long-term performance. Compared to ML-only models, our approach learns from both real and simulated experiences, enhancing robustness. The significant improvement in AUC and sensitivity indicates that the system is better at detecting diverse arrhythmias. Moreover, embedding the decision engine on the edge (TinyML) meets MCPS constraints: real-time operation is achieved without cloud dependency, addressing critical latency and reliability requirements. These findings align with trends in the literature: advanced CPS increasingly exploit MORL for multi-criteria control and DT feedback for safety and optimization. Our work unifies these advances and validates them in a medical context. In quantitative terms, the paired tests yield p-values <0.01 for all key metrics, confirming the improvements are statistically significant.

7 Conclusion

We have presented a comprehensive framework for autonomic self-decision making and self-optimization in medical CPS. By integrating reinforcement learning, multi-objective optimization, and digital twin simulation, the system achieves truly autonomous operation under uncertainty. Our case-study on arrhythmia detection shows that the hybrid approach significantly outperforms conventional methods in both accuracy and real-time responsiveness. The multi-layer architecture – from edge ML to cloud-based RL and DT – provides a scalable, extensible foundation for future CPS applications. This work addresses critical gaps in CPS research by delivering a unified architecture that seamlessly combines decision-making and optimization. It demonstrates that CPS can self-manage complex tasks in dynamic environments, paving the way for safer and more efficient healthcare systems. The framework is domain-agnostic and can be applied to other MCPS applications (e.g. smart ICU, autonomous surgery robots) with appropriate models. Future work will explore learning in truly online settings with human-in-the-loop, and extending the digital twin with multi-physics patient modelsCPS applications.

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