

Adaptive Residential Load Control with Smart Scheduling

CONTROL SYSTEMS AND INSTRUMENTATION ENGINEERING PROGRAM

Papop Chawanchaisuan, Tanawin Satang
Advisor: Dr. Tanagorn Jennawasin

Abstract

This project presents an Adaptive Residential Load Control with Smart Scheduling system to reduce electricity costs via Time-of-Use (TOU) pricing, enhance energy efficiency, and maintain resident comfort using Machine Learning and the Internet of Things (IoT). The system employs an automated adaptive scheduling algorithm to learn consumption behaviors and manage electrical loads based on real-time grid conditions and energy prices. The methodology involved the design of a 1:10 scaled condominium prototype. A hybrid approach is used to manage 13 appliances, utilizing physical hardware within the office and a simulation framework elsewhere for cost-effective performance evaluation. Data is transmitted via MQTT to a Supabase database and processed using a Python-based scheduling engine. The system utilizes Multi-Agent Reinforcement Learning (MARL) with the Q-learning algorithm to optimize scheduling to achieve a balance between energy costs and resident comfort [2]. Furthermore, to mitigate high costs of Building Information Modeling (BIM) software, Blender was used to develop a 3D Digital Twin through a React-based web user interface, enabling effective real-time monitoring and residential energy management [1].

Keywords: Adaptive Load Control, Multi-Agent Reinforcement Learning (MARL), Time-of-Use (TOU), 3D Digital Twin, Internet of Things (IoT)

Introduction

Increasing electricity demand and dynamic Time-of-Use (TOU) pricing require smarter residential energy management. Conventional systems often lack flexibility in responding to changing energy prices and operating conditions, leading to inefficient electricity usage and higher costs. This project proposes an Adaptive Residential Load Control with Smart Scheduling system that integrates Machine Learning, Internet of Things (IoT), and adaptive decision-making to optimize household energy consumption. The system manages electrical loads based on scheduling strategies and system conditions, aiming to reduce costs, improve efficiency, and maintain resident comfort for more sustainable smart home energy management.

Methodology

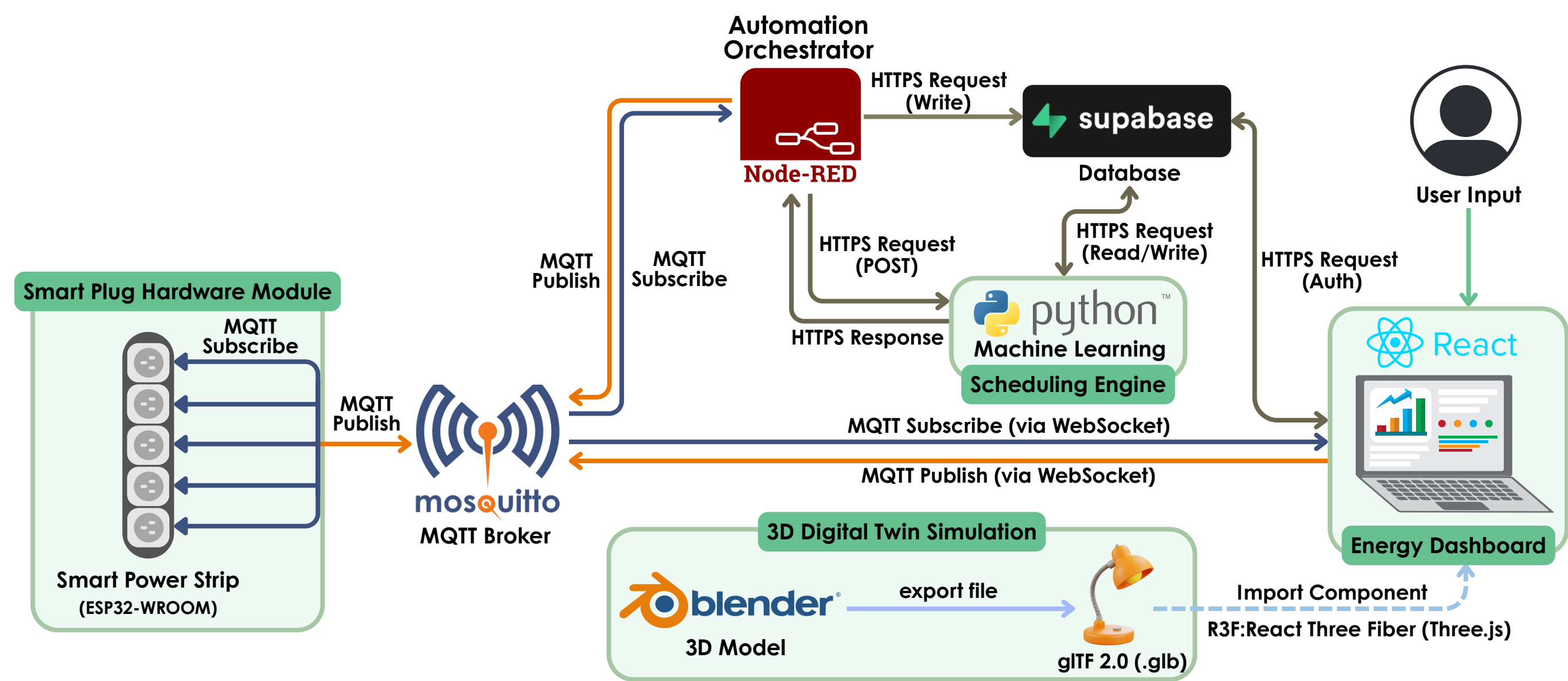


Figure 1: System Architecture

The process begins with designing a system architecture that bridges the physical and virtual worlds (Physical-to-Digital) to create a smart home environment in the form of a hybrid platform encompassing 13 types of devices under test (DUTs). This is achieved through the integration of real devices and behavioral simulations. The process starts with a smart power strip, which acts as the edge node, using the PZEM-004T module in conjunction with an ESP32 to measure real-time electricity consumption. This is done in parallel with the operation of simulated electrical devices, designed using behavioral simulation logic, to generate realistic electricity usage data at the software level. All electrical device usage data is then transmitted via the MQTT protocol, and the data flow is managed by Node-RED for storage in the Supabase database. The status is then synchronized with a 3D digital twin dashboard to create an accurate simulation that fully reflects the behavior of the devices in all dimensions [1].

Table 1: Devices under Test (DUT)

No	Device	Types of appliances	Type	Quantity
1	Ceiling Lights	Inflexible	Hardware + Simulation	24
2	Bedside Lamp	Inflexible	Hardware	1
3	Laptop	Inflexible	Hardware	1
4	Ceiling Fan	Inflexible	Simulation	1
5	Desk Lamp	Inflexible	Simulation	1
6	Television	Inflexible	Simulation	1
7	Electric Stove	Inflexible	Simulation	1
8	Refrigerator	Inflexible	Simulation	1
9	Air Conditioner	Power-Flexible	Simulation	3
10	Table Fan	Time-Flexible	Hardware	1
11	Washing Machine	Time-Flexible	Simulation	1
12	Dryer	Time-Flexible	Simulation	1
13	Air Purifier	Time-Flexible	Simulation	1

The core of the system is the management of 13 types of devices under test (DUTs), categorized by their flexibility of use to enable the AI system to analyze them appropriately:

- Inflexible Load:** Devices whose usage cannot be changed.
- Power Flexible Load:** Devices whose power consumption can be adjusted.
- Time Flexible Load:** Devices whose usage time can be postponed.

This electricity usage data is then analyzed in conjunction with Tariff Type 1 (Residential Service) in a Time-of-Use (TOU) format, which divides pricing into On-Peak and Off-Peak periods to determine the most cost-effective operating times.

Table 2: Tariff Type 1

Tariff Type 1: Residential service applicable to households, temples, monasteries, and other religious institutions (including their associated premises) connected through a single electricity meter.

Rate Category 1.2: Time of Use (TOU) Rate

Charges are calculated based on consumption time intervals.

Time of Use (TOU) Tariff	Energy Charge (THB/Unit)	Service Charge (THB/Month)
On-Peak 09:00-22:00	5.7982 THB/Unit	24.62 THB/Unit
Off-Peak 22:00-09:00	2.6369 THB/Unit	

Note: Applicable for voltage levels below 22 kilovolts (kV).

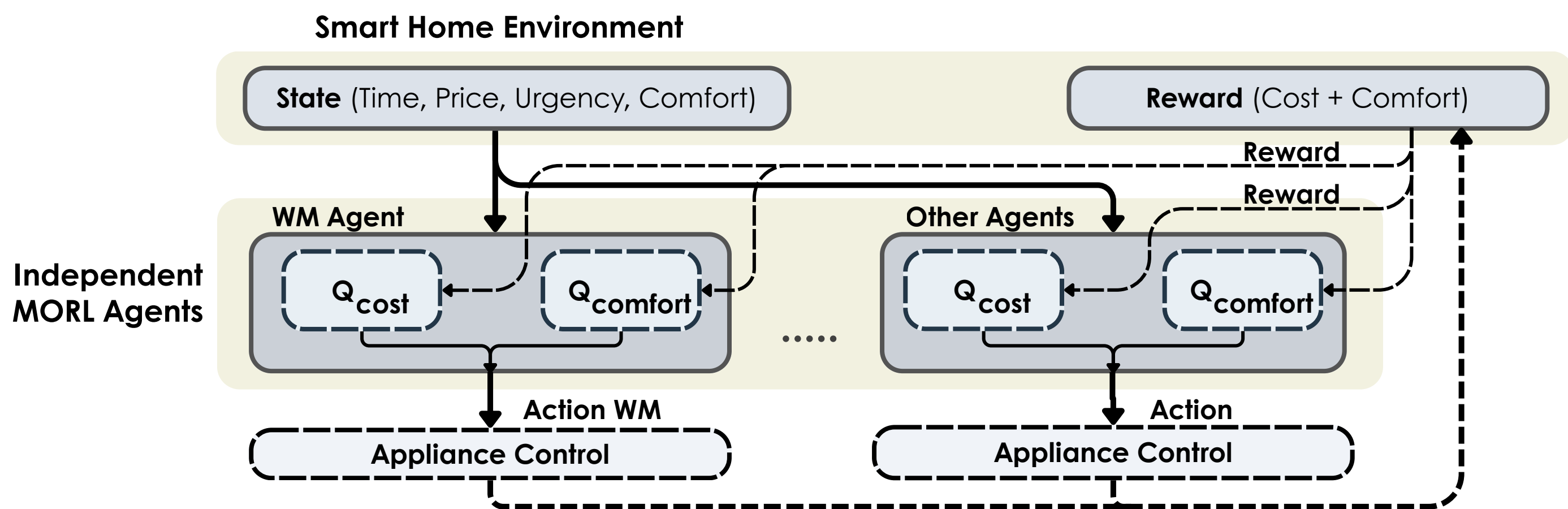


Figure 2: Multi-Agent MORL with Independent Q-Learning

Smart Home Environment – A hybrid platform integrates 13 appliances through hardware and simulation. The environment encodes key system states, including hour index, TOU price bin, urgency and comfort level for each agent.

Multi-Agent MORL Framework – Each controllable appliance acts as an independent agent in a Multi-Agent Reinforcement Learning framework. Using Q-learning, agents evaluate actions and coordinate adaptive scheduling to improve energy efficiency under changing conditions [2].

Reward Design – A weighted reward function evaluates electricity cost, comfort preservation, and operational constraint penalties to guide adaptive scheduling decisions.

Results



Figure 3: 3D Digital Twin Interface for Real-time Energy Monitoring and Control

The system successfully integrates and displays data in real-time via a 3D Digital Twin Dashboard. The 3D model responds with animations that correspond to the actual operating status of the equipment (e.g., fan and drum rotation speeds), along with highly accurate power consumption (wattage) readings from both the actual and simulated equipment.

Table 3: Algorithm Performance

The MORL agent optimizes the balance between energy savings and user comfort based on defined weights

Cost Weight	Energy Cost (THB/day)	Cost Reduction	Time Deviation	Temp Deviation
0.9 (Cost)	50.28	57.64%	0.188	0.831
0.5 (Balanced)	108.63	8.49%	0.188	0.417
0.1 (Comfort)	118.72	0% (Baseline)	0	0

Cost-priority saves up to 57.64% but compromises comfort. Lower deviations indicate better alignment with user preferences.

Conclusion

This project developed an intelligent load control system integrating IoT and Multi-Agent Reinforcement Learning (MARL) via a Hybrid Digital Twin platform. The system optimizes device scheduling based on Time-of-Use (TOU) rates, achieving electricity cost reductions of up to 57.64% in energy-saving mode and 8.49% in balanced mode, demonstrating a significant advancement in efficient and sustainable residential energy management.

References

- [1] G. Piras et al., "Smart Buildings and Digital Twin," Applied Sciences, 2025.
- [2] S.-J. Chen et al., "Smart Home Energy Management using Multiobjective Reinforcement Learning," IEEE Access, 2021.